Adaptive Learner-Centric LMS: Enhancing Student Engagement and Personalized Learning Experiences

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Abstract: - The continuous evolution of educational technology necessitates adaptive, learner-centric systems tailored to individual student needs. This paper introduces an advanced approach to enhancing student engagement and personalized learning through the integration of four key components: Personalized Quiz Generation, Adaptive Mind Map Generation, Study Techniques, and Document Assistant. Each component addresses critical challenges in modern education, including real-time adaptability, cognitive load management, and personalized learning support. The system incorporates evidence-based study techniques, such as the Pomodoro Technique and adaptive workload balancing, to optimize focus, retention, and productivity. Leveraging cutting-edge technologies such as Large Language Models (LLMs) and microservices architecture, the proposed system ensures a seamless and scalable learning environment. This paper details the system's design, implementation, and potential educational impact, emphasizing its role in improving learning efficiency and student outcomes.

Keywords: *retrieval-augmented generation, personalized quiz generation, adaptive mind maps, study techniques, cognitive load management.*

1. Introduction

The rapid advancement of digital technology has significantly transformed the landscape of education, leading to the emergence of adaptive learning systems. These systems redefine traditional educational paradigms by shifting away from the conventional one-size-fits-all, teacher-centric approach and embracing personalized, student-centered learning experiences. Learning Management Systems (LMS) have long served as the backbone of digital education, providing centralized platforms for course management and content delivery [1]. Traditional LMS are widely used in education, but they often struggle to meet the evolving needs of modern learners. Their rigid structure, lack of flexibility, and limited customization options make it difficult to provide engaging and personalized learning experiences [2].

The integration of Artificial Intelligence (AI) in educational technology is transforming LMS platforms, making them more adaptive and data-driven. AI-powered LMS platforms use technologies such as Large Language Models (LLMs), machine learning algorithms, and real-time analytics to improve content delivery, assessments, and learner engagement [3]. By analyzing student behavior, performance metrics, and interaction patterns, these systems can adjust educational content in real-time, ensuring a personalized learning experience that aligns with each learner's strengths, weaknesses, and progress [1].

Despite these advancements, many LMS platforms still face significant limitations. A major issue is their reliance on static content formats, like PDFs, which require users to manually download, store, and manage materials with little to no interactivity [2]. Additionally, most systems offer limited interface customization, making it difficult for learners to adjust reading layouts, font sizes, or interactive elements to suit their preferences [4].

Another drawback is the lack of built-in tools for essential study techniques. Features like note-taking, time management strategies (such as the Pomodoro technique), and focus-enhancing tools like background music often require separate applications. This leads to a fragmented workflow, disrupting concentration and reducing learning efficiency [4]. Furthermore, many LMS platforms fail to track learning history or user activity, preventing students from easily revisiting past sessions and reinforcing their knowledge [2].

Educators also face significant challenges in designing and managing learning content efficiently. Creating and updating lessons, quizzes, and assessments is often a time-consuming process, taking away valuable time from more strategic teaching efforts [2]. Additionally, the lack of integration between different learning modalities such as visual aids, adaptive feedback, and structured study plans limits the ability to create an engaging and effective learning environment [4].

To address these issues, this study proposes an AI-driven adaptive LMS that leverages advanced personalization techniques to enhance content delivery, learner engagement, and study efficiency. The system enables users to upload PDFs, which are then processed to extract and structure content for interactive use. Learners can navigate materials by chapter, generate personalized mind maps based on study prompts, create adaptive quizzes tailored to their proficiency levels, and interact with content through an AI-powered chat interface.

The platform also includes built-in session management tools, such as real-time study tracking, dynamic break scheduling, and an integrated focus music player, all designed to improve concentration and retention. Additionally, real-time analytics identify areas where learners struggle, adjusting content recommendations dynamically to address knowledge gaps. Automated content linking further enhances organization by seamlessly connecting related resources, reducing manual effort, and ensuring a structured learning path.

With an intuitive user interface optimized for ease of use and engagement, this AI-powered LMS provides a seamless and productive learning experience, allowing students to interact with educational materials in a more personalized and efficient way.

However, several challenges must be addressed to optimize the functionality and scalability of adaptive LMS platforms. Content extraction from various document formats must be precise to maintain the contextual integrity of the educational materials. Adaptive assessments must strike the right balance between challenge and reinforcement to ensure optimal learning progression. Additionally, ensuring system efficiency at the user-demand scale remains a crucial consideration [2]. This study aims to explore and address these challenges by developing an AI-driven LMS that enhances educational outcomes through intelligent content adaptation, personalized assessments, and integrated engagement tools.

In summary, the proposed AI-driven adaptive LMS represents a transformative step in digital education, integrating intelligent personalization, real-time feedback, and interactive learning tools. By fostering deeper engagement, improving retention, and streamlining study processes, this system empowers learners to take control of their education, while enhancing overall learning efficiency [1]. As the demand for personalized education grows, adaptive LMS platforms have the potential to bridge educational disparities, support lifelong learning, and prepare individuals for success in the ever-evolving global workforce.

2. Background and Literature Review

The evolution of LMS has significantly reshaped the educational landscape, transitioning from basic platforms focused primarily on content delivery and administrative functions to more dynamic, personalized learning environments. In the early stages of e-learning, LMS platforms were primarily designed for content distribution, administrative management, and basic communication tools. However, these traditional LMS platforms were criticized for their rigidity and inability to meet the diverse needs of individual learners. Studies have highlighted that these systems offered limited interaction, failed to accommodate various learning styles, and lacked adaptability to the learner’s progress or preferences [1]. Consequently, the limitations of traditional LMS platforms have led to the emergence of more sophisticated learning environments characterized by adaptive and intelligent learning technologies. These systems emphasize personalized, dynamic learning experiences tailored to each student’s needs rather than merely serving as content delivery mechanisms.

Recent research on adaptive learning systems has underscored the importance of personalization in enhancing student engagement and knowledge retention. A significant development in this field has been the incorporation of Artificial Intelligence (AI) into education. AI-enabled LMS platforms have introduced a wide range of new capabilities, including real-time performance tracking, personalized assessments, and adaptive learning paths that automatically adjust based on student performance [1]. The integration of AI enables these systems to analyze large amounts of student data and deliver customized content tailored to each learner's unique needs.

Kardan and Conati [5] demonstrated that intelligent tutoring systems (ITS) that adapt in real-time to a student's performance result in higher retention rates. Furthermore, personalized assessments significantly improve students' understanding compared to static, one-size-fits-all quizzes.

Building upon the concept of adaptive assessments, Shute and Spector [6] introduced the concept of stealth assessments. These assessments are seamlessly integrated into learning activities, allowing for continuous evaluation of student performance without the pressure of formal testing. The implementation of stealth assessments reduces test anxiety, thereby enhancing engagement with the content. This approach addresses the often-overlooked issue of test-related stress and contributes to a more positive and productive learning experience. These advancements have paved the way for more responsive and engaging educational tools that align with the cognitive and emotional needs of learners.

Despite these advancements, traditional LMS platforms continue to suffer from key limitations, particularly in providing real-time student support. In conventional systems, students often experience delays in receiving instructor feedback, which can lead to frustration, disengagement, and a decline in learning effectiveness. To address this issue, researchers have explored the integration of AI-powered chatbots as a solution for immediate, round-the-clock assistance. These chatbots provide explanations, answer questions, and suggest additional resources. Molnár et al. [7] found that students who interacted with AI chatbots received faster responses compared to traditional discussion forums, leading to improved engagement and a more interactive learning experience. Zawacki-Richter et al. [8] further emphasized that AI-driven tutoring systems could significantly reduce cognitive overload by helping students navigate complex content and learning paths. However, current AI-driven chatbots often rely on predefined response patterns, making them less adaptable to the diverse needs of students. The ability of these systems to engage in real-time, contextual conversations and adjust to individual learner requirements remains an area of ongoing research [9].

In addition to AI-driven support, visual learning techniques have gained considerable attention in digital education. Mind mapping, as a visual learning strategy, has been shown to improve knowledge retention, enhance conceptual understanding, and increase recall rates [10]. Mind maps assist students in organizing information, establishing connections between concepts, and visualizing relationships that may be difficult to grasp through traditional linear methods. Davies [11] demonstrated that students who utilized mind maps performed better in terms of conceptual understanding and retention compared to those relying solely on traditional note-taking methods. The integration of mind map generation tools within LMS platforms has the potential to enhance the learning process by automating the creation of visual diagrams based on learner progress. However, current research on mind-mapping tools within LMS platforms remains limited, particularly concerning real-time adaptability and personalization. Most existing systems rely on static templates and fail to adjust to learners' evolving needs, leaving significant opportunities for further exploration in AI-driven, dynamic mind map personalization [12].

Effective time management is a critical factor in optimizing learning outcomes in online education. Students engaged in distance learning often struggle with maintaining focus and structuring study sessions efficiently. Research in cognitive psychology and neurobiology emphasizes that sustained attention requires balancing cognitive load management, neurobiological recovery mechanisms, and evidence-based break scheduling. The Pomodoro technique, which segments study sessions into focused intervals followed by brief breaks, has been widely recognized for improving concentration and academic performance. Cirillo [13], the creator of the Pomodoro technique, demonstrated that individuals using this method exhibited enhanced focus and efficiency. Costales et al. [14] demonstrated that applying the Pomodoro Technique as a productivity tool in online learning can enhance learning outcomes, as evidenced by their study on learning assessments.

From a cognitive load theory (CLT) perspective, effective time management must account for intrinsic load (the complexity of material), extraneous load (distractions or inefficient study design), and germane load (cognitive resources dedicated to schema formation) [15]. Extended study sessions can increase extraneous cognitive load due to environmental distractions and working memory limitations. For instance, multitasking during complex tasks like studying biochemical pathways can potentially raise extraneous load, impairing schema development. This is because extraneous load arises from factors that do not contribute to learning, such as poorly designed study environments or multitasking, which can overwhelm working memory and hinder the formation of meaningful connections between concepts [16]. To counteract this, an adaptive time management framework dynamically adjusts work-break cycles based on real-time cognitive load indicators, such as engagement levels, reaction times, and accuracy metrics. When cognitive fatigue is detected evidenced by slowed responses or decreased performance the system shortens study intervals and extends breaks to facilitate memory consolidation and prevent burnout. Conversely, when focus remains high, work periods can be extended within optimal cognitive thresholds.

Despite the demonstrated benefits of structured time management, existing LMS platforms lack seamless integration of adaptive work-break cycles informed by cognitive science and AI-driven analytics. The potential for personalized, real-time workload balancing aligned with individual cognitive states remains an underexplored area in educational technology. Future research should investigate how intelligent time management systems can enhance learning efficiency by dynamically optimizing study intervals based on neural and behavioral indicators.

Despite advancements in adaptive learning, AI-powered support, and cognitive-based learning tools, most existing LMS platforms fail to integrate these innovations comprehensively. Alhazmi et al. [4] analyzed contemporary LMS systems and identified several gaps, including the lack of real-time assessment adjustments, insufficient AI-driven support, and an absence of structured time management strategies. These shortcomings hinder the development of truly personalized and effective learning experiences. Current LMS platforms still rely on static content delivery, fail to adapt to learners' evolving needs, and do not incorporate cognitive-based learning strategies in a meaningful way.

The proposed research introduces an Adaptive Learner-Centric LMS that leverages AI-driven features to enhance student engagement and learning efficiency. This system dynamically adjusts learning paths based on student performance, providing real-time feedback and personalized recommendations for improvement. It incorporates automated mind mapping with resource linking, enabling students to visualize concepts interactively and track their progress. Additionally, an AI-powered chatbot offers real-time, personalized assistance to reduce cognitive overload and enhance learner engagement. To support effective time management, the system integrates Pomodoro-based study techniques, helping students maintain focus and productivity. By combining these elements, the LMS creates a personalized, interactive, and adaptive learning environment that optimizes student success.

This research aims to bridge the gap between traditional, static LMS platforms and more personalized, data-driven learning environments. By integrating these innovative features, the proposed LMS will not only improve student engagement and retention but also optimize learning outcomes, offering a more holistic and adaptive approach to modern education.

3. System Design and Methodology

3.1. System Overview

The proposed system adopts a modular architecture to deliver personalized and adaptive learning experiences. It integrates multiple components that collectively optimize the study process, content delivery, and knowledge retention. Each module is designed to address specific aspects of the learning journey, including cognitive workload management, quiz generation, mind map creation, and conversational AI support. The system leverages advanced technologies such as machine learning, natural language processing (NLP), and retrieval-augmented generation (RAG) to provide a dynamic and personalized learning environment. The following sections detail the design and functionality of each core component, highlighting the methodologies and algorithms used to enhance user engagement and performance.

3.2. System Architecture

As shown in Fig. 1 the system architecture consists of interconnected components that streamline study material generation. It begins with PDF data extraction using the Adobe PDF API, followed by three core modules: Mind Map Generation using Mermaid.js, Quiz Generation powered by LLM models, and Intent-Aware Document Interaction for user queries. The system integrates external services like Google Search API and DALL-E for enriched content. Data is stored in MongoDB for quiz results and Weaviate DB for semantic search. The User Interface allows users to upload documents, take quizzes, view mind maps, and interact with documents while managing study sessions and personalized notes.

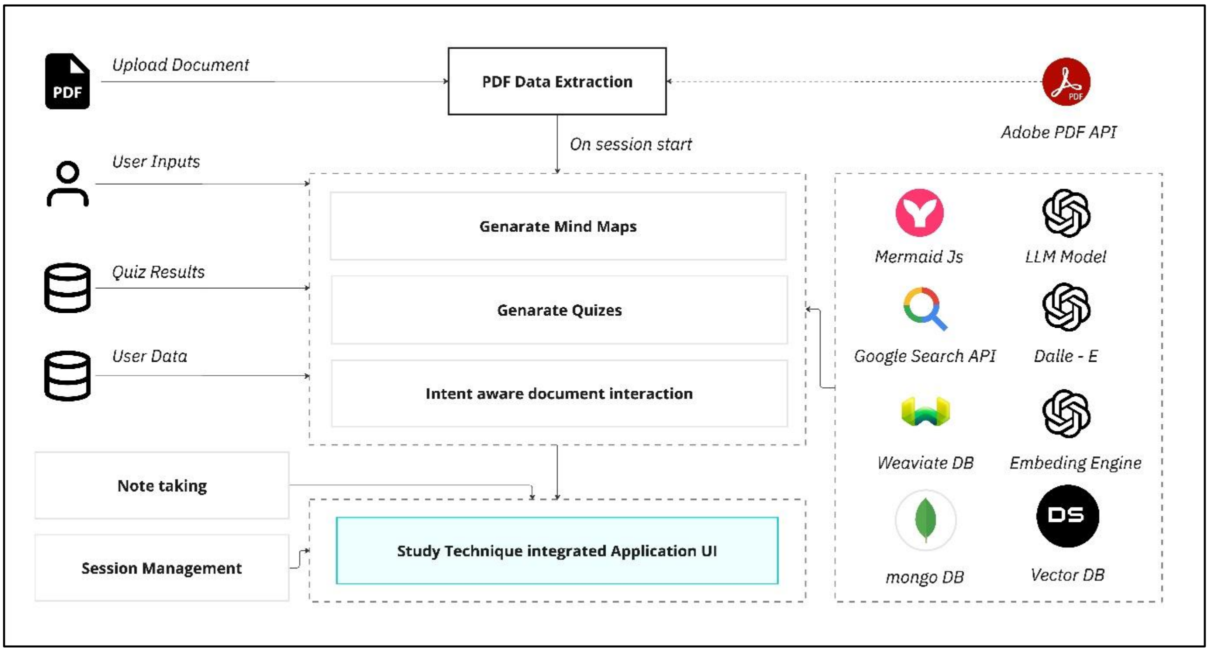

Fig. 1 System Architecture

3.3. Study Techniques and Cognitive Load

To create an efficient learning environment, the system incorporates a Cognitive Load Management Module that monitors cognitive fatigue and engagement levels. It follows a modular architecture that integrates workload balancing algorithms, structured study techniques, and an interactive learning interface. The backend handles session management and cognitive load computations, while the frontend provides real-time session controls, visual timers, and interactive study tools. Additionally, an integrated background music module helps sustain focus and mental clarity during study sessions, as illustrated in Fig. 2.

3.3.1. Adaptive Workload Balancing

The system dynamically segments study sessions into structured intervals using an intelligent workload balancing algorithm. Users can choose from multiple break calculation methods, and the system adapts work-break cycles based on cognitive load indicators such as engagement levels, reaction times, and performance metrics. If cognitive fatigue is detected, the system shortens work intervals and extends breaks to prevent burnout. Conversely, if high focus is maintained, study periods are extended within optimal cognitive limits. This adaptive approach ensures efficient learning while minimizing mental exhaustion.

3.3.2. Break Calculation Algorithms and Their Limitations

Initially, two break calculation approaches were explored. Due to the limitations of these methods, the Dynamic Work-Break Adjustment Algorithm was selected as the optimal solution.

3.3.2.1. Fixed-Time Algorithms

Progressive Pomodoro - begins with longer work periods that gradually shorten over time. However, this method assumes a uniform cognitive load, which may not be suitable for all learners [17][18].

Flowtime Technique - allows uninterrupted focus, with breaks based on task completion rather than fixed intervals. While this flexibility helps, it does not account for cognitive fatigue levels, potentially leading to overexertion [19][20].

3.3.2.2. Predefined Interval Algorithm

25:5 Pomodoro - Short sessions with 25-minute work periods followed by 5-minute breaks. This method may be too rigid for longer study sessions.

50:10 Intervals - Medium-length sessions with 50-minute work periods followed by 10-minute breaks. Although effective, it lacks adaptability based on real-time fatigue levels.

90:20 Intervals - Designed for deep work but does not accommodate fluctuations in concentration and energy levels.

3.3.3. Dynamic Work-Break Adjustment Algorithm

This advanced model dynamically adjusts both work and break durations in real time based on session length and user energy levels. Unlike fixed-time approaches, this method adapts to the user's cognitive fluctuations, ensuring sustained productivity and mental well-being. The process works as follows

3.3.3.1. Initial Work Period Assignment

The system sets an initial work period based on session goals. For example, in an 8-hour session, the first work cycle may be 50 minutes.

3.3.3.2. Real-Time Monitoring

The system continuously tracks engagement through mouse movements, window focus, and interaction patterns.

3.3.3.3. Dynamic Adjustments

If signs of cognitive fatigue (e.g., reduced engagement, slower response times) are detected, the system gradually reduces work duration while increasing break periods. If a user maintains high engagement levels, the system extends work intervals within cognitive limits.

3.3.3.4. User-Controlled Interruptions

If an interruption occurs, the system recalculates break schedules and rebalances the remaining session time. Users can manually log interruptions, allowing the system to learn individual work patterns over time.

3.3.3.5. Adaptive Break Scheduling

Breaks are extended progressively based on energy depletion, ensuring effective recovery before the next work cycle. If users voluntarily extend their work time, subsequent breaks adjust proportionally to maintain cognitive balance.

3.3.4. Real-Time Session Tracking and Adaptation

The system actively tracks user engagement through mouse movements, window focus time, and interaction patterns. If inactivity is detected, the session is paused, and break schedules are recalculated. Users can manually log interruptions or allow the system to adjust breaks automatically. Additionally, the system enables session extensions, recalculating break durations accordingly. Detailed session history logs provide insights into study patterns, interruptions, and engagement levels.

3.3.5. Background Music and Cognitive Optimization

To further support cognitive efficiency, the system integrates a background music module. Research suggests that certain types of music, such as low-tempo instrumental tracks, can improve focus and reduce mental fatigue. The

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system provides curated playlists tailored for study and break intervals, ensuring a distraction-free auditory environment. Users can select preferred playlists or allow the system to suggest tracks based on session type. During breaks, the music transitions to more relaxing tunes to facilitate mental recovery before the next study period.

By overcoming the limitations of fixed-time and predefined interval methods, the Dynamic Work-Break Adjustment Algorithm ensures a fully adaptive study experience. Combined with structured scheduling, real-time monitoring, and focus-enhancing music, the Adaptive Learner-Centric LMS provides an efficient and personalized learning environment. This methodology optimizes cognitive performance, prevents burnout, and enhances long-term knowledge retention, making it a comprehensive solution for effective study management.

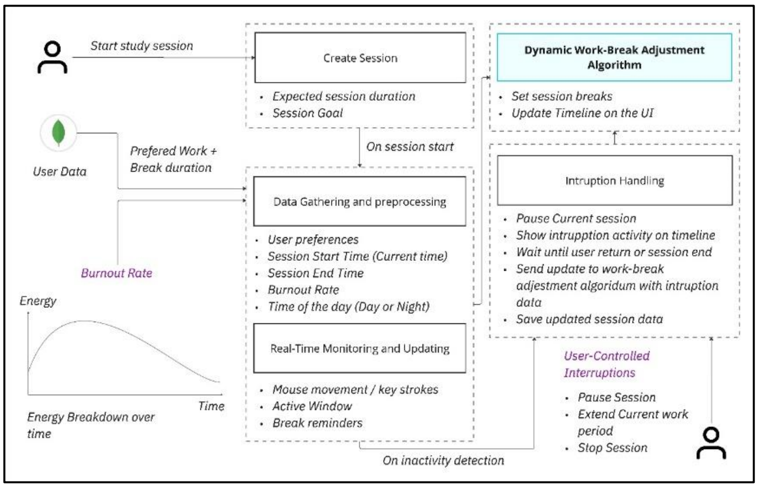

Fig. 2 Session Managment Component

3.4. Adaptive Quiz Generation

The proposed system generates adaptive quizzes tailored to individual user performance, as illustrated in Fig. 3. The methodology involves retrieving content from PDFs, preprocessing it, and utilizing OpenAI's language model to generate multiple-choice questions (MCQs) and short-answer questions.

3.4.1. Content Extraction and Preprocessing

The system extracts text from PDF documents, filtering out non-text elements, empty values, and undefined entries. This preprocessing ensures that only structured and relevant content is used in question generation, thereby improving accuracy and contextual relevance.

3.4.2. Question Generation with Bloom's Taxonomy

Quiz questions are generated using OpenAI's model, incorporating Bloom's Taxonomy for difficulty-based categorization. The difficulty level is set on a scale of 0 to 100, aligning with different cognitive skill levels:

- 0–30 (Lower-order skills) – Remembering & Understanding (Basic recall, factual knowledge).
- 31–60 (Intermediate difficulty) – Applying & Analyzing (Problem-solving, conceptual application).
- 61–100 (Higher-order skills) – Evaluating & Creating (Critical thinking, synthesis of ideas).

Separate models generate MCQs and short-answer questions:

- MCQs include one correct option with three distractors, ensuring structured assessments.
- Short-answer questions test conceptual depth and explanatory ability.

3.4.3. Quiz Data Storage and Retrieval

To facilitate efficient storage and retrieval of quiz data, the system employs:

- MongoDB for MCQs, enabling efficient document-based querying.

- Weaviate for short-answer questions, leveraging semantic search and vector embeddings for similarity-based retrieval.

3.4.4. Answer Validation Mechanism

- MCQ validation is performed by directly comparing user responses with stored correct answers in MongoDB.
- Short-answer validation utilizes Weaviate's semantic search, employing OpenAI's ADA embedding model to compute similarity between user responses and the correct answer.

3.4.5. Adaptive Quiz Personalization

The quiz difficulty dynamically adjusts based on user performance. The first attempt begins with a default difficulty level of 50. In subsequent quizzes, the difficulty is adapted as follows:

- High performance (≥75%) → Difficulty is increased, progressing towards higher-order skills (Analyzing, Evaluating, Creating).
- Low performance (<50%) → Difficulty is decreased, focusing on reinforcing fundamental concepts (Remembering, Understanding, Applying).

This adaptive learning mechanism ensures an optimized progression, tailored to individual competency levels.

3.4.6. AI-Driven Feedback and Performance Enhancement

The system provides personalized feedback using an AI-generated prompt that analyzes user performance. It highlights:

- Strengths: Areas where the user performed well.
- Weaknesses: Topics needing improvement.
- Actionable Suggestions: Targeted recommendations for better understanding.

The AI processes quiz responses, summarizing performance metrics, listing incorrect answers with corrections, and identifying common errors. It then offers tailored strategies for improvement, ensuring adaptive learning and continuous progress.

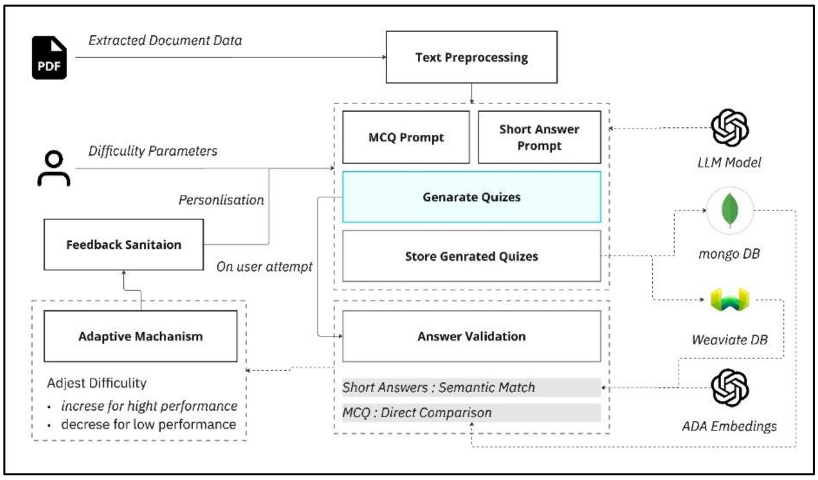

Fig. 3 Quiz Component

3.5. Adaptive Personalized Mind Maps

3.5.1. Problem Definition

In the field of personalized adaptive mind map generation, a significant challenge exists in providing users with dynamic, relevant, and personalized educational content. The key difficulties stem from the need to generate mind maps that can adapt to varying user levels and preferences while ensuring that the content remains accurate, contextually appropriate, and aligned with user learning outcomes. The primary objectives of this research are:

1. To utilize retrieval-augmented generation (RAG) techniques to enhance the mind map generation process by integrating up-to-date knowledge from external sources, ensuring that users receive contextually relevant content.
2. To leverage large language models (LLMs) for natural language understanding and generation to personalize the content based on individual user quizzes and learning progress.
3. To build an adaptable resource linking system where mind map nodes can be enriched with external resources that support further exploration of topics, ensuring that the generated mind map evolves based on the user's learning needs.

The core challenges addressed in this study include:

1. Ensuring content accuracy by reducing LLM hallucinations through the use of retrieval-augmented generation techniques.
2. Personalizing content dynamically based on user interaction with the system, including quiz results and current knowledge levels.
3. Enabling continuous learning through adaptive mind map generation that integrates feedback loops to adjust the complexity and details of the map.

3.5.2. Design Rationale

The design of the system integrates multimodal data pipelines for mind map creation, combining user-generated content (like quiz responses) with semantic retrieval techniques that source external knowledge to enhance the user's experience. The system follows a context-aware design to dynamically adjust the mind map's structure and content to the user's expertise and learning progression. The rationale behind this approach includes:

1. User-Centric Personalization: By using quiz results and previous mind map interactions, the system tailors its output to suit the user's level and needs, ensuring that the generated mind map remains relevant and digestible.
2. Dynamic Knowledge Enhancement: Incorporating retrieval-augmented generation allows for the system to fetch relevant resources and include them in the mind map, enriching the user's understanding of the content.
3. Integration with External Resources: By linking mind map nodes to external resources (via Google Search API or other sources), the system offers avenues for further learning, making it not only a tool for visualization but also for deeper exploration.

3.5.3. System Design and Architecture

The architecture of the Personalized Adaptive Mind Map Generator system is structured to facilitate real-time data integration, dynamic learning, and accurate mind map generation, as shown in Fig. 4.

3.5.3.1. Pipeline 1: Knowledge Extraction and Data Preprocessing

This pipeline handles the extraction of data from various sources, including PDFs, quiz results, and user profiles. Using Adobe's API, the system extract PDF content and convert it into structured JSON format. This data is stored in MongoDB, associated with the user's unique userId and documentId to ensure persistent storage of the mind maps and progress.

The semantic data extraction involves parsing and organizing text data into easily searchable vector representations using techniques like Word2Vec or BERT embeddings.

Once processed, the content is indexed and stored, ensuring easy retrieval during the generation phase.

3.5.3.2. Pipeline 2: Retrieval-Augmented Generation (RAG)

For personalized mind map generation, user queries (e.g., their learning topics or quiz results) are first semantically processed using an LLM like OpenAI's GPT model. This semantic rewriting optimizes queries for retrieving the most relevant information from the stored knowledge base.

A retrieval mechanism pulls relevant content based on the user's query and knowledge level, which is used to enrich the mind map's nodes. This process integrates retrieved external resources, like online articles, studies, or additional PDF content, to ensure the mind map reflects the most current and relevant information.

Contextual relevance is ensured by ranking retrieved content based on its similarity to the query and adjusting for user-specific details like learning goals or quiz performance.

3.5.3.3. Pipeline 3: Mind Map Generation and Adaptation

After retrieving the relevant content, the system merges the data into a coherent structure that forms the mind map. This structure includes nodes representing key concepts and links to related resources, all tailored to the user's learning journey.

Adaptation mechanisms are applied where the generated mind map is dynamically adjusted based on the user's previous interactions with the system, ensuring that content complexity and structure adapt over time as the user advances.

3.5.4. Integration with Quiz Data

To make the system adaptive and context-sensitive, the mind map generation process integrates quiz data as an input mechanism. This allows the system to:

Highlight areas of weakness in the user's knowledge by visually marking nodes related to incorrect answers or incomplete concepts.

Adjust the content complexity based on the user's level, ensuring that the generated mind map is neither too simple nor too complex, but instead, it matches the user's current understanding. Store the latest three quiz-based mind maps, allowing users to track their progress over time and revisit previous mind maps to reinforce learning.

3.5.5. System Integration and Performance Optimization

- The system processes textual documents to generate structured and meaningful mind maps, ensuring clarity and coherence in knowledge representation. Extracted content is stored in a structured format, enabling efficient parsing and retrieval for mind map generation.
- Efficient resource linking is ensured by integrating the Google Search API and other resources to provide context-aware links for further reading, enabling users to explore more about any specific node or topic.
- To maintain optimal performance, the system employs efficient indexing and retrieval mechanisms to ensure fast and accurate access to stored knowledge. By structuring content effectively within the database, the system minimizes retrieval latency, providing a smooth and responsive user experience.

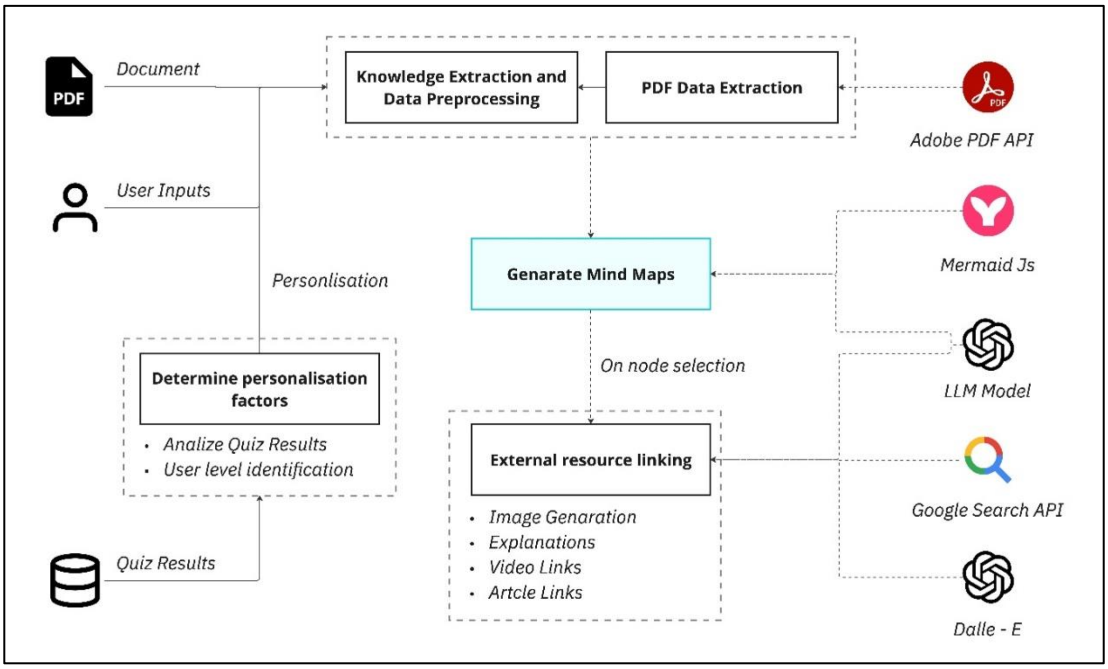

Fig. 4 Mind Map Component

3.6. AI-Driven Document Assistant

The AI Document Assistant of the system utilizes an intent-based response generation approach powered by RAG, ensuring that student queries are accurately interpreted and addressed in a structured, contextually relevant manner. Upon receiving a query, the system first identifies the user's intent based on predefined categories, such as summarization, table generation, quiz creation, concept simplification, topic explanation, and code snippet generation, as shown in Fig. 5. The system utilises prompt engineering to achieve this by guiding the AI model's response format.

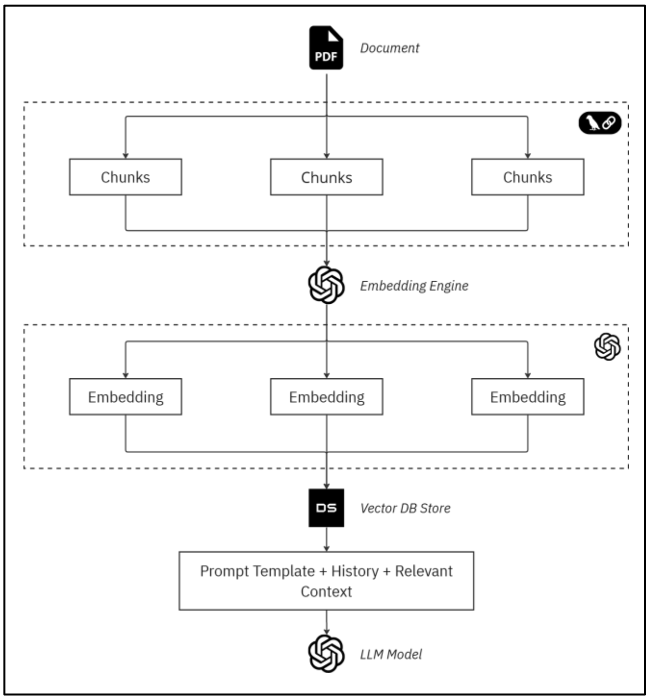

Fig. 5 Document Assistant Component

3.6.1. Initializing the Vector Store

The system leverages LangChain's PDFLoader class to extract text from PDFs, enabling efficient document-based querying. However, since the implementation is built on LangChain.js, it lacks support for image-based text extraction (OCR), a capability available in the Python version of LangChain. Consequently, only textual content is processed, while embedded images and scanned text remain inaccessible.

After extracting the document text, the system applies a chunking process to divide the text into smaller, contextually coherent segments. The chunk size is set to 1536, with an overlap of 300, ensuring that key contextual information is preserved for smoother retrieval and improved response accuracy. This step enhances retrieval efficiency by allowing the system to access relevant portions of the document without processing the entire text at once. Once chunked, each segment is converted into a numerical representation using the OpenAI embedding model, which captures semantic relationships within the text. These embeddings are then stored in DataStax Astra DB, a vector database optimized for similarity-based retrieval.

3.6.2. Querying and Context Retrieval

When a student submits a query, the system first evaluates its adherence to content guidelines using OpenAI's Moderation Chain. If the query is flagged as inappropriate, the system issues a warning and does not proceed further.

If the query is deemed appropriate, the system retrieves relevant context from the vector store through a similarity search. This process identifies and extracts the most relevant document sections based on their semantic similarity to the user's query.

Once the relevant context is retrieved, it is combined with the chat history and the student's question to construct a structured input for the language model. Before invoking the model, the system applies a predefined prompt template, ensuring that responses are accurate, contextually relevant, and aligned with the student's inquiry.

3.6.3. Prompt Engineering

To ensure the system effectively understands and responds to student queries, a structured approach to prompt engineering was implemented. A key component of this approach was identifying the various ways students might interact with the LLM. Queries can vary in intent, such as summarizing information, generating code snippets, creating comparison tables, simplifying concepts, or generating quiz questions. By recognizing these diverse intents, the system was able to tailor its response generation process to meet the specific needs of each query.

To achieve this, a combination of prompt engineering techniques was employed. Initially, the system analyses the student's query to determine its intent. Based on this classification, the appropriate structured prompt is applied, guiding the LLM's response to ensure it aligns with the query's specific needs.

For example, if a student requests a summary, the system selects a prompt that instructs the LLM to generate key points in a bullet list. If the query involves a comparison, a structured Markdown table format is used to present the information clearly. Similarly, when a request for a code snippet is made, the system formats the response using code blocks to ensure proper syntax and readability.

By incorporating intent-aware prompting and structured formatting, the system significantly enhances response accuracy, clarity, and usability. This methodology ensures that responses are contextually relevant and formatted optimally for educational purposes, thereby improving the overall student experience with the AI Document Assistant.

4. Results and Discussion

The primary goal of the system integrated into the Learning Management System (LMS) is to enhance the accuracy, contextual relevance, and robustness of generated educational content, such as mind maps, quizzes, and resource linking. By leveraging advanced machine learning models along with external APIs like the Google Search API, the system aims to provide learners with improved educational tools that adapt to their needs, support personalized learning paths, and offer more accurate content generation.

In addition to content generation, the system integrates a Chat Assistant using Langchain to facilitate interactive learning and answer questions in real-time. It also incorporates the Pomodoro technique to optimize learning sessions and improve user productivity through effective time management.

4.1. Evaluation of System Performance and Impact

4.1.1. Performance of Proprietary Models

In this section, the performance of GPT-4o and GPT-4 models is explored, particularly in the contexts of mind map generation, quiz generation, image generation, and the Pomodoro Technique for time management. Additionally, the use of the Mermaid.js library in mind map generation is examined and how it contributes to enhancing the quality of generated maps.

4.1.1.1. Answer Correctness

Key Metric: The correctness of answers generated by GPT-4 and GPT-4o directly affects the accuracy and reliability of the results produced, particularly in educational applications such as quiz generation and mind map construction.

Findings:

- GPT-4 and GPT-4o showed significant improvements in correctness after retrieval augmentation. For instance, GPT-4 started with a correctness score of 0.73 and increased to 0.79, while GPT-4o improved from 0.75 to 0.81.
- This improvement in correctness indicates that the models, when augmented with retrieval-augmented generation (RAG) techniques, were able to better understand and answer complex queries, leading to more accurate and useful outputs in both text and visual generation tasks.

- Implication for Mind Map Generation: In mind map generation, the accuracy of the information provided within the generated nodes is paramount. For example, when a user inputs a question or topic, the system must generate accurate, coherent connections between concepts. The improvements in correctness help ensure that the generated maps reflect accurate relationships between topics.

- Implication for Quiz Generation: Correctness in quiz generation is key for ensuring that the right answers are provided to users. With retrieval augmentation, GPT-4 and GPT-4o models can generate quiz questions and answers that are not only accurate but also highly relevant to the user's learning context. This is crucial for personalized and effective assessments.

4.1.1.2. Answer Relevancy

Key Metric: Answer relevancy measures how well the generated content aligns with the query context. In both mind map and quiz generation, ensuring that the content is highly relevant to the user's intent is essential.

Findings:

1. GPT-4 demonstrated an increase in relevancy from 0.87 to 0.90, while GPT-4o improved from 0.86 to 0.89 after the introduction of retrieval augmentation. These increases are indicative of the models' ability to better align their answers with the given context.

2. Retrieval augmentation plays a significant role in ensuring that both GPT-4 and GPT-4o maintain a high level of relevance in their responses. This is particularly useful in applications where the models need to answer highly specific queries or generate content that requires a deep understanding of context.

3. Implication for Mind Map Generation: In the context of mind map generation, relevancy ensures that nodes are linked to each other in meaningful and contextually appropriate ways. When generating complex maps based on educational content or user input, high relevancy ensures that the system identifies the most pertinent relationships between ideas, making the map more accurate and useful.

4. Implication for Quiz Generation: For quiz generation, relevancy ensures that questions and answers are not only accurate but also contextually aligned with the intended subject matter. For example, when a user is learning about a specific topic, GPT-4 and GPT-4o will generate questions that are aligned with that specific knowledge domain. This makes the quiz more focused and relevant to the learner's needs.

4.1.1.3. Contextual Utilization

Key Metric: Contextual utilization measures how well the model utilizes the provided context when generating responses. In other words, it refers to how effectively the model incorporates the relevant information from retrieved documents or resources.

Findings:

- GPT-4o showed a substantial improvement in context recall, reaching 0.99 after retrieval augmentation, which signifies its ability to effectively use the retrieved context to generate relevant outputs.

- GPT-4 also showed a significant improvement in context precision, increasing from 0.83 to 0.88. This indicates that the model is better at using the retrieved context in a focused and relevant manner, avoiding unnecessary or irrelevant details.
- Implication for Mind Map Generation: Contextual recall and precision are critical in mind map generation, as they ensure that the model accurately selects the most relevant concepts and relationships to display in the map. By using the right context to form links between nodes, GPT-4 and GPT-4o generate mind maps that more accurately reflect the intended structure and content of the input data. For instance, when generating a map based on an academic subject, the models can ensure that related concepts are grouped together logically and that irrelevant concepts are excluded.

- Implication for Quiz Generation: For quiz generation, contextual recall ensures that the system can pull in the most relevant material from the background context, creating questions that are not only correct but also tightly aligned with the user's current level of understanding. By focusing on the right context, the model can tailor quiz content to specific topics or subtopics, improving the learning experience.

4.1.2. Integration of the Session Management

The integration of session management in the system builds upon traditional time management techniques, enhancing them with real-time cognitive load monitoring and adaptive learning strategies. Unlike conventional Pomodoro-based methods, this approach incorporates an advanced Cognitive Load Management Module, which dynamically adjusts work and break intervals based on user engagement and fatigue levels.

Key Metric: The effectiveness of this methodology is measured by its ability to optimize cognitive performance, sustain user focus, and prevent burnout while improving task completion times.

Findings:

- The implementation of an Adaptive Workload Balancing system significantly improved user engagement and productivity. Unlike fixed-time Pomodoro cycles, developed system dynamically adjusts work intervals based on cognitive load indicators such as reaction time, interaction frequency, and sustained focus levels.

- Users experienced enhanced focus and reduced mental fatigue through the system's Dynamic Work-Break Adjustment Algorithm. This method surpasses traditional fixed-interval techniques by adapting work-break cycles in real time to match user energy levels.

- The integration of real-time engagement tracking, including mouse movement analysis and window focus detection, allowed for intelligent session adjustments. If cognitive fatigue was detected, break durations were automatically extended to facilitate recovery.

- A user-controlled interruption feature allowed individuals to manually log distractions, helping the system learn personal work patterns and recalibrate break schedules accordingly.

- The incorporation of a background music module contributed to cognitive optimization by maintaining a focus-friendly auditory environment. By dynamically adjusting playlists based on session phases, the system helped sustain concentration during work periods and facilitated relaxation during breaks.

- Through structured study intervals, real-time tracking, and adaptive scheduling, users achieved improved retention rates and more efficient study sessions. The system's flexibility ensured that study durations aligned with cognitive endurance, minimizing the risk of burnout while maximizing learning efficiency.

4.1.3. Additional Resource Linking

To further enhance the user's learning experience and the context for mind map generation, the system integrates Google Search API, LLMs, and DALL·E for additional resource linking. These tools help provide relevant external resources, such as articles, images, and related content, that complement the mind maps and quizzes generated by the GPT-4 models. The aim is to create a more immersive and comprehensive learning environment by offering users easy access to a variety of resources directly linked to the generated content.

4.1.3.1. Resource Relevance and Quality

Key Metric: The relevance and quality of linked resources, which are provided in response to the user's queries or mind map nodes, are critical in offering value-added content for deepening understanding and expanding knowledge.

Findings:

1. Google Search API: The integration of the Google Search API allows the system to dynamically fetch relevant external resources. When a user interacts with a node in the generated mind map, the system queries Google for resources linked to that topic, returning articles, papers, tutorials, and more. These resources are carefully filtered and presented to users as they navigate their mind maps, enriching their knowledge base with real-time, updated information from trusted sources.

- Example: When a user clicks on a "Machine Learning" node in their mind map, the system retrieves articles, papers, and videos from credible websites, providing a more comprehensive learning experience.

2. LLMs (Large Language Models): In addition to Google Search, LLMs are used to generate contextual explanations, definitions, or summaries for specific nodes within the mind map. When a user interacts with a node, the LLM assesses the context and generates an in-depth explanation or a concise definition of the concept, helping the user better understand the material.

- Example: When a user selects the "Deep Learning" node, the system may use an LLM to generate a tailored summary of deep learning, its importance, and key techniques involved.

3. DALL·E: For visual enrichment, DALL·E is used to generate images associated with specific mind map nodes. These images are aligned with the topic at hand and can serve to visually represent abstract concepts, making it easier for the user to grasp complex topics.

- Example: When the user clicks on a node related to "Artificial Intelligence," DALL·E generates a related image, such as an illustration of neural networks or a robotic entity, visually enriching the mind map.

4. Impact on Mind Map Generation: By combining Google Search API, LLMs, and DALL·E, the system not only generates accurate and contextually relevant mind maps but also provides interactive and rich multimedia content that enhances the user's understanding. The added resources help clarify concepts, answer queries, and provide both textual and visual explanations, making the mind map experience much more engaging and informative.

- Example: In a mind map about Computer Science, each node could be dynamically linked to multiple resources (articles, videos, images, summaries) related to topics like algorithms, machine learning, or software development, helping the user explore topics in depth without leaving the platform.

4.1.3.2. User Interaction and Personalization

Key Metric: User interaction with the additional resources is a key factor in assessing the utility and effectiveness of the resource linking system. Personalization of the linked resources, based on the user's progress and preferences, further enhances the user experience.

Findings:

1. Personalization: The system utilizes user behavior data (such as the user's learning level, past interactions, and preferences) to personalize the linked resources. For example, if a user struggles with certain topics, the system can present additional resources like beginner-level articles or tutorials to help bridge knowledge gaps.
• Example: If a user frequently interacts with nodes related to "Linear Algebra" but struggles to understand the material, the system might prioritize beginner-friendly resources, interactive tutorials, or even video lectures that are more suitable for the user's current knowledge level.

2. LLM Personalization: By utilizing LLMs with a focus on personalization, the system can adapt the generated content (e.g., explanations or summaries) based on the user's prior interactions and quiz results. This allows the content to align with the user's learning progress and objectives, improving retention and understanding.
• Example: If the user is performing poorly on quizzes related to "Neural Networks," the system can adapt by providing more focused and simplified explanations for the concepts, offering resources that break the topic down into easier-to-understand components.

3. Impact on Mind Map Generation: Personalization through resource linking makes the system more interactive and responsive to the user's needs. The user is not only guided through relevant external resources but also has the ability to deepen their understanding based on the resources they choose to explore further.

4.1.4. Chatbot Response Quality

The authors evaluated the effectiveness of two different prompt engineering approaches, as described in Table 1, for the RAG chatbot designed to assist students in self-directed learning. The chatbot responses were evaluated based on accuracy, structure, clarity, and relevance to the document content for both prompts against 40 questions.

Table 1 Simple Prompt and Intent-Aware Structured Prompt

	Simple Prompt	**Intent-Aware Structured Prompts**
Prompt Engineering Technique	Zero-Shot	Combination of Zero-Shot, Chain of Thoughts, Meta Prompting and Prompt Chaining
Description	Instructions to assume the role and provide responses strictly within the context of the document.	Recognizes the user's intent and formats responses accordingly, strictly within the document context (e.g., summaries, tables, quizzes, or explanations).

Key findings:

1. The Simple Prompt approach showed signs of hallucination and inconsistency with the inability to respond to certain queries stating the query was out of scope when it was not.
2. Intent Aware Structured prompt performed better in structured responses in formatting summaries, tables, code snippets and quizzes.
3. Both prompts performed well in providing factually accurate answers, but the intent-aware structured prompt provided better clarity and organization.
4. Handling of unrelated queries was similar for both prompts, but the intent-aware structured prompt provided a more polished response.

5. Conclusion and Future Work

This study introduces an Adaptive Learner-Centric Learning Management System (LMS) that leverages artificial intelligence-driven technologies to enhance personalized learning, engagement, and knowledge retention. The system incorporates artificial intelligence-powered mind maps to visually structure complex concepts, dynamically generated quizzes that adapt to individual performance levels, and real-time progress tracking to provide insights into learning achievements and knowledge gaps. A cognitive load management module is designed to optimize study sessions, with future enhancements focusing on machine learning models for fatigue prediction, artificial intelligence-driven music recommendations, and biometric feedback integration, including heart rate variability and eye tracking. An artificial intelligence-driven document assistant further supports learning by generating structured responses such as summaries, tables, and code snippets, with future improvements aimed at refining prompt structures and incorporating image-based text extraction. The LMS ensures seamless integration with educational tools and features a user-friendly interface for both students and instructors. Future research will explore predictive analytics for identifying learning gaps, natural language processing-based interactive assistants for advanced student support, and the integration of immersive technologies such as augmented reality and virtual reality. Additionally, scalability enhancements will be prioritized to accommodate a growing user base across diverse learning environments.

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